Computing, Information & Communications Technology (CICT) Program

Intelligent Systems (IS) Project

Intelligent Data Understanding (IDU)

Wildfire Detection & Prediction

Jerry Miller (P.I.), NASA, Code 586, Greenbelt, MD

Dr. Kirk Borne (Co-I), GMU, Greenbelt, MD

Dr. Brian Thomas, RSTX, Greenbelt, MD

Dr. Zhenping Huang, RSTX, Greenbelt, MD

Yuechen Chi, GMU, Greenbelt, MD

Donna McNamara, NOAA-NESDIS, Camp Springs, MD

George Serafino , NOAA-NESDIS, Camp Springs, MD

NOAA'S HAZARD MAPPING SYSTEM

NOAA's Hazard Mapping System (HMS) is an interactive processing system that allows trained satellite analysts to manually integrate data from 3 automated fire detection algorithms corresponding to the GOES, AVHRR and MODIS sensors. The result is a quality controlled fire product in graphic (Fig 1), ASCII (Table 1) and GIS formats for the continental US.

Figure 1. Hazard Mapping System (HMS) Graphic Fire Product for day 5/19/2003

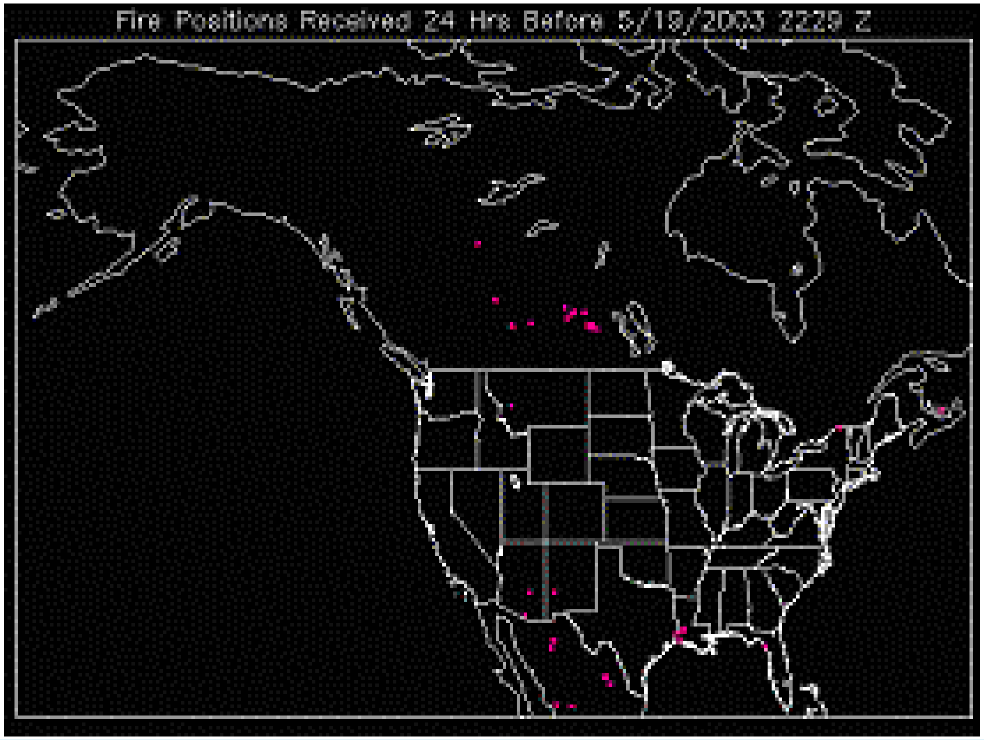


Table 1 Hazard Mapping System (HMS) ASCII Fire Product

OLD FORMAT

Lon,	Lat
-80.531,	25.351
-81.461,	29.072
-83.388,	30.360
-95.004,	30.949
-93.579,	30.459
-108.264,	27.116
-108.195,	28.151
-108.551,	28.413
-108.574,	28.441
-105.987,	26.549
-106.328,	26.291
-106.762,	26.152
-106.488,	26.006
-106.516,	25.828

NEW FORMAT (as of May 16, 2003)

Lon,	Lat,	Time,	Satellite,	Method of Detect
-80.597,	22.932,	1830,	MODIS AQUA,	MODIS
-79.648,	34.913,	1829,	MODIS,	ANALYSIS
-81.048,	33.195,	1829,	MODIS,	ANALYSIS
-83.037,	36.219,	1829,	MODIS,	ANALYSIS
-83.037,	36.219,	1829,	MODIS,	ANALYSIS
-85.767,	49.517,	1805,	AVHRR NOAA-16,	FIMMA
-84.465,	48.926,	2130,	GOES-WEST,	ABBA
-84.481,	48.888,	2230,	GOES-WEST,	ABBA
-84.521,	48.864,	2030,	GOES-WEST,	ABBA
-84.557,	48.891,	1835,	MODIS AQUA,	MODIS
-84.561,	48.881,	1655,	MODIS TERRA,	MODIS
-84.561,	48.881,	1835,	MODIS AQUA,	MODIS
-89.433,	36.827,	1700,	MODIS TERRA,	MODIS
-89.750,	36.198,	1845,	GOES,	ANALYSIS

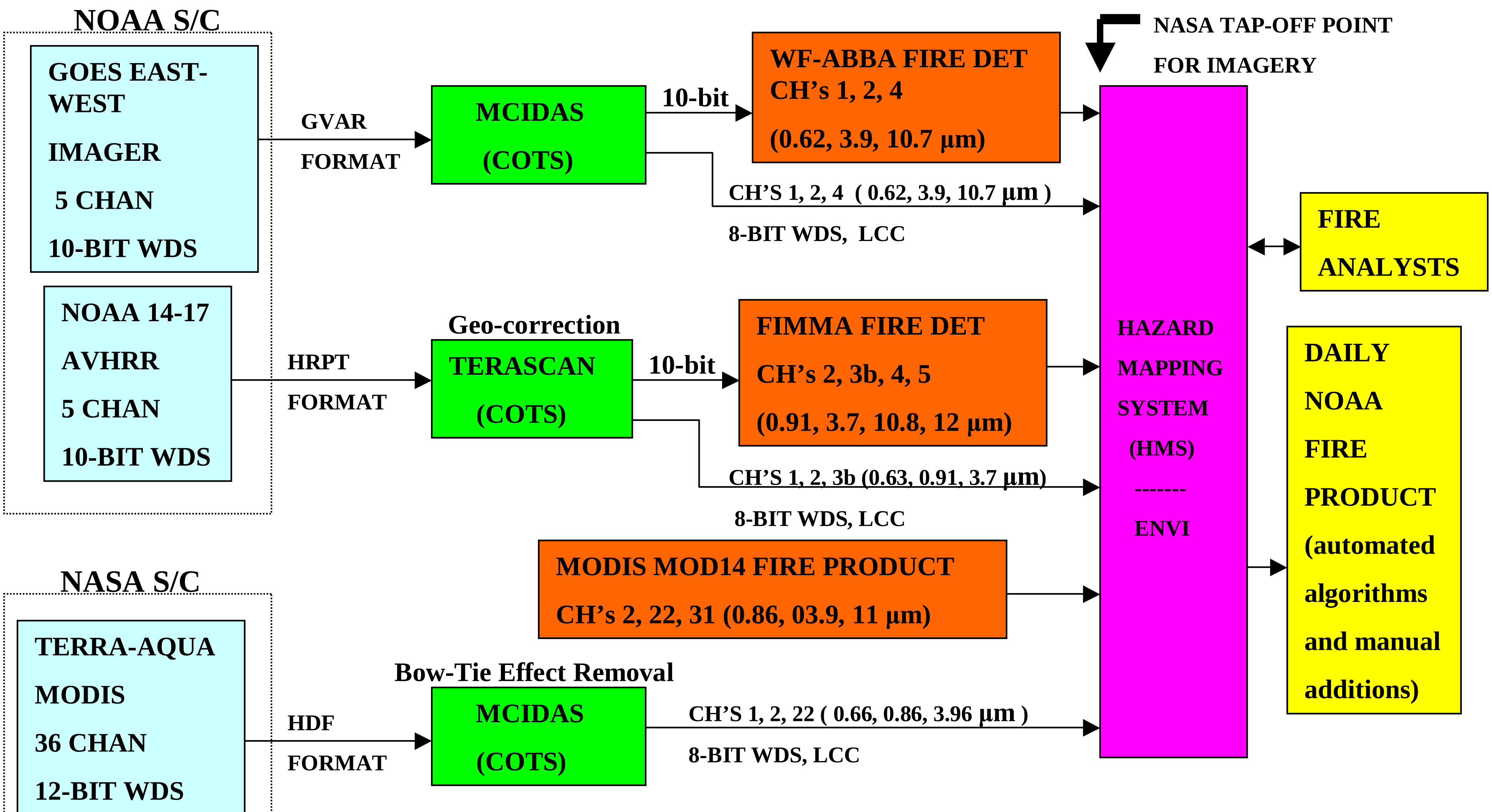
OVERALL TASK OBJECTIVES

Mimic NOAA-NESDIS Fire Analysts' subjective decision making and automated fire detection algorithms with a Neural Network to:

- improve automation & consistency
- allow NESDIS to expand coverage globally

FIGURE 2 NOAA-NESDIS FIRE DETECTION SYSTEM

WF-ABBA = Wildfire Automated Biomass Burning Alg   FIMMA = Fire Identification Mapping and Monitoring Alg

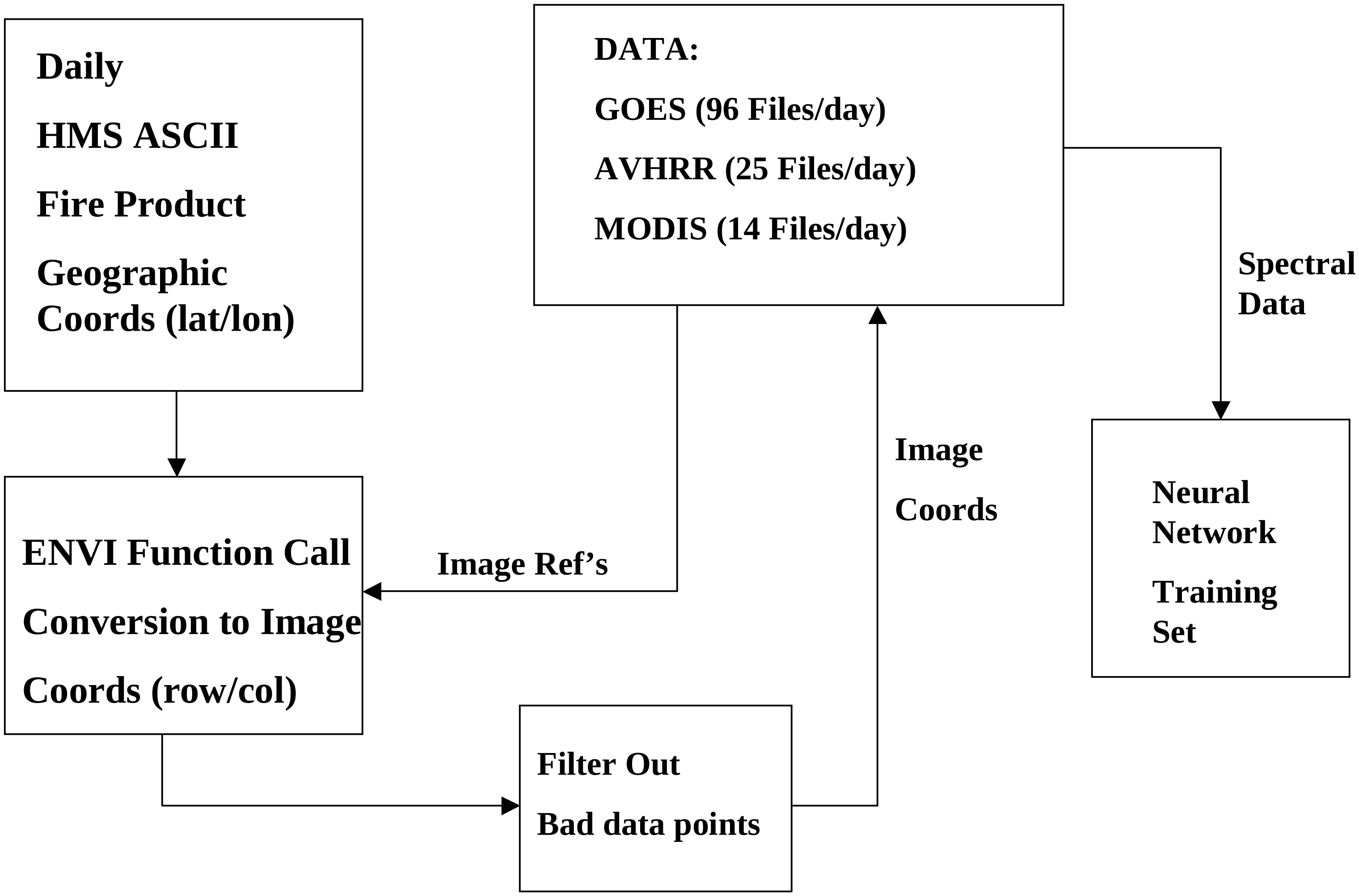


LCC = Lambert Conformal Conic Projection   MCIDAS = Man Computer Interactive Data Access System

SOURCES OF SUBJECTIVITY IN FIRE ANALYSTS DECISION MAKING

- Fire is not burning very hot, small in areal extent
- Fire is not burning much hotter than surrounding scene
- Dependency on Analysts' "aggressiveness" in finding fires
- Determination of false detects

FIGURE 3 SIMPLIFIED DATA EXTRACTION PROCEDURE



Neural Network Training Set Generation

1. Initially, confine analysis to homogenous geographic region (see Figs 4-6)

2. Local minima search on each HMS fire location to fix image position of fire

3. Break up 24Hr period into N time segments, e.g.:

Let T1 = 0000 – 0600 T3 = 1200 – 1800

T2 = 0600 – 1200 T4 = 1800 – 2400

4. Search for peak negative intensity in 3-4 μm band (see Figs 7-9) for each fire location and each time segment to fix time of fire

5. With fire fixed in position and time, extract spectral data for all channels

6. For a single channel and single fire location per line, after normalization:

I_{T1}	I_{T2}	I_{T3}	I_{T4}	TARGET
0.232862	0.127503	0.069222	0.103664	0
0.974467	0.291175	0.259978	0.845269	1
		•		
		•		
		•		

Figure 4 Initial Geographic Study Regions (homogenous ground cover)

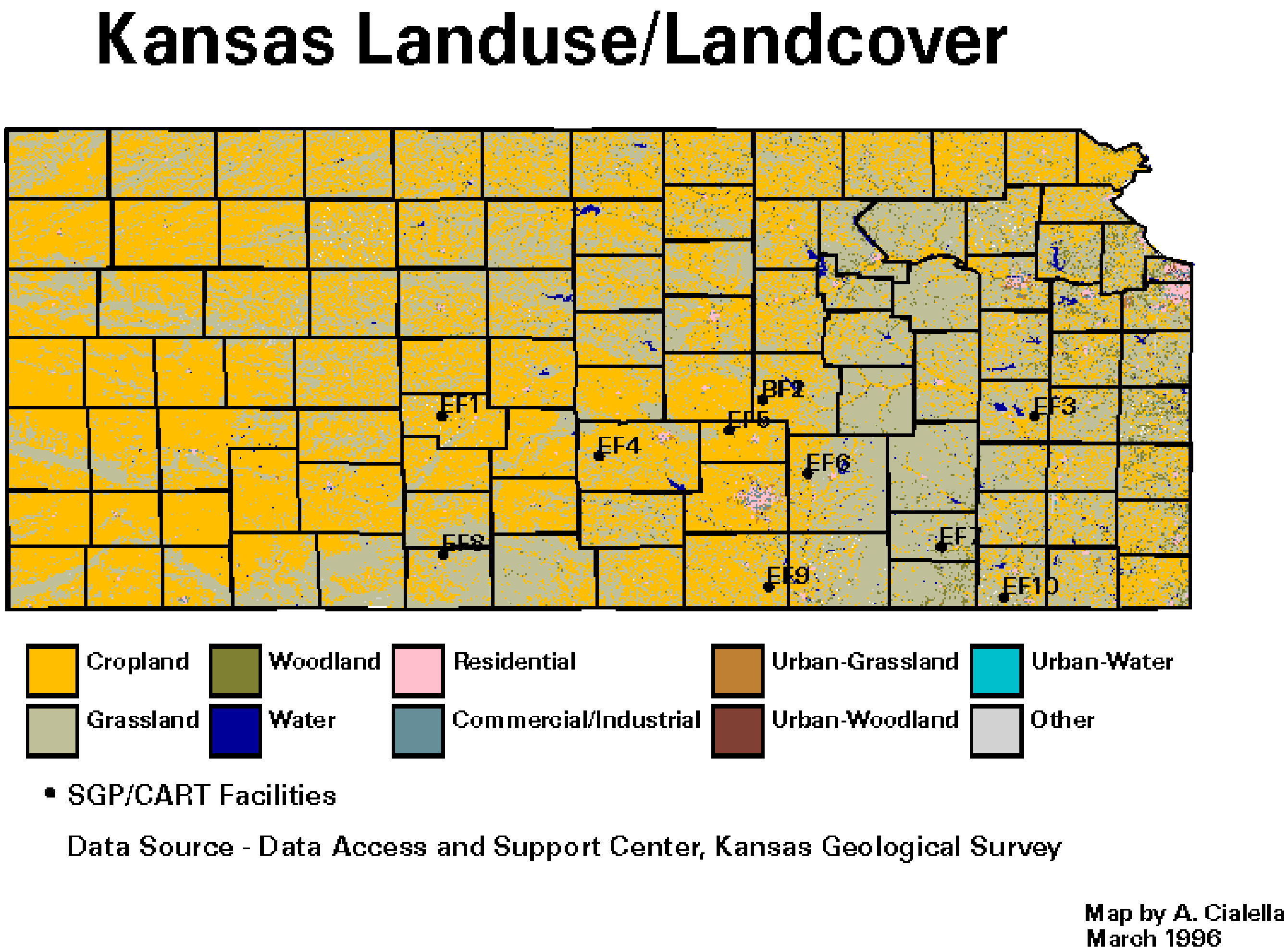


Figure 5 Initial Geographic Study Regions (homogenous ground cover)

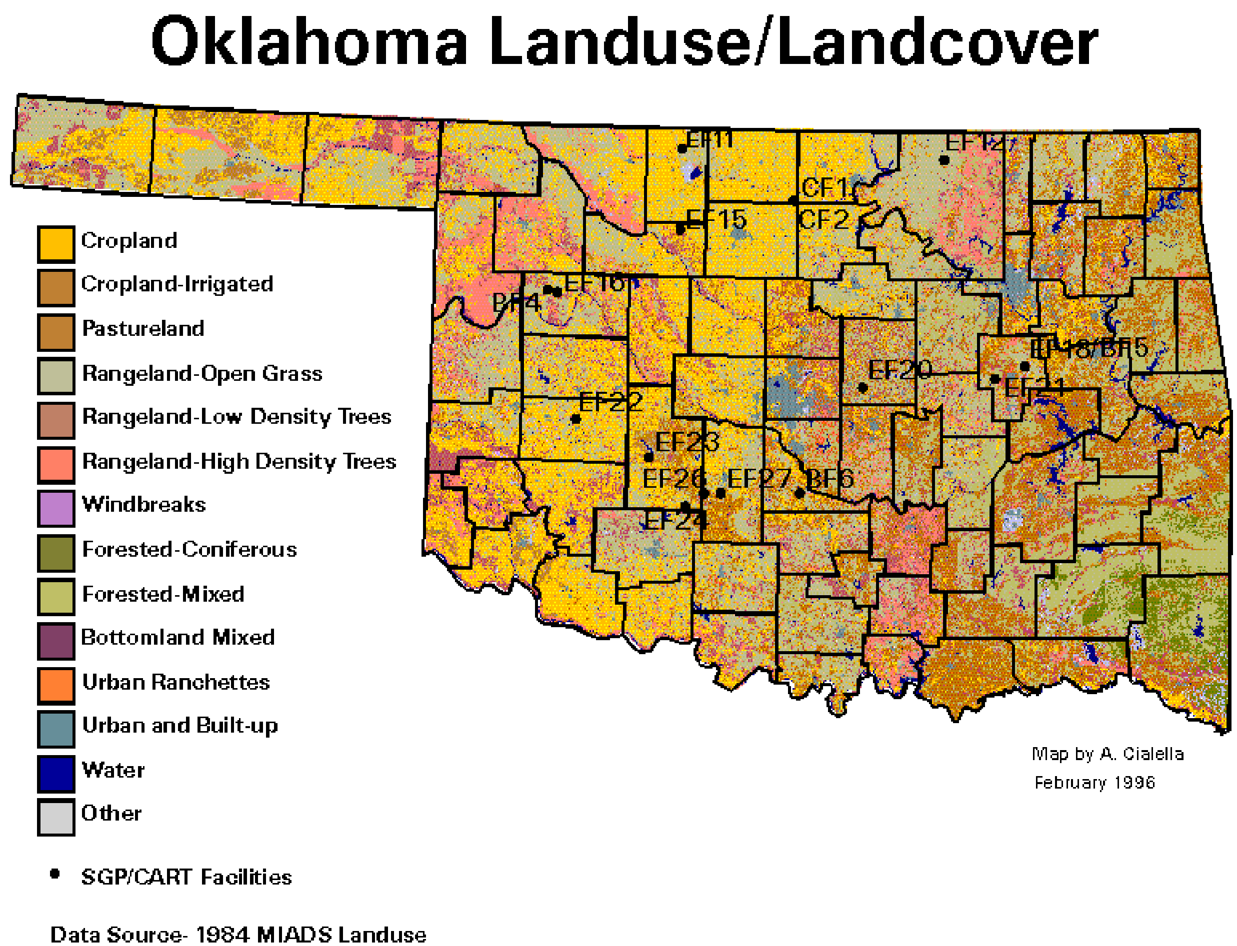


Figure 6 DECISION REGIONS AND BOUNDARIES FOR HIGHLY IDEAL SCATTER PLOT CLUSTERING PATTERNS

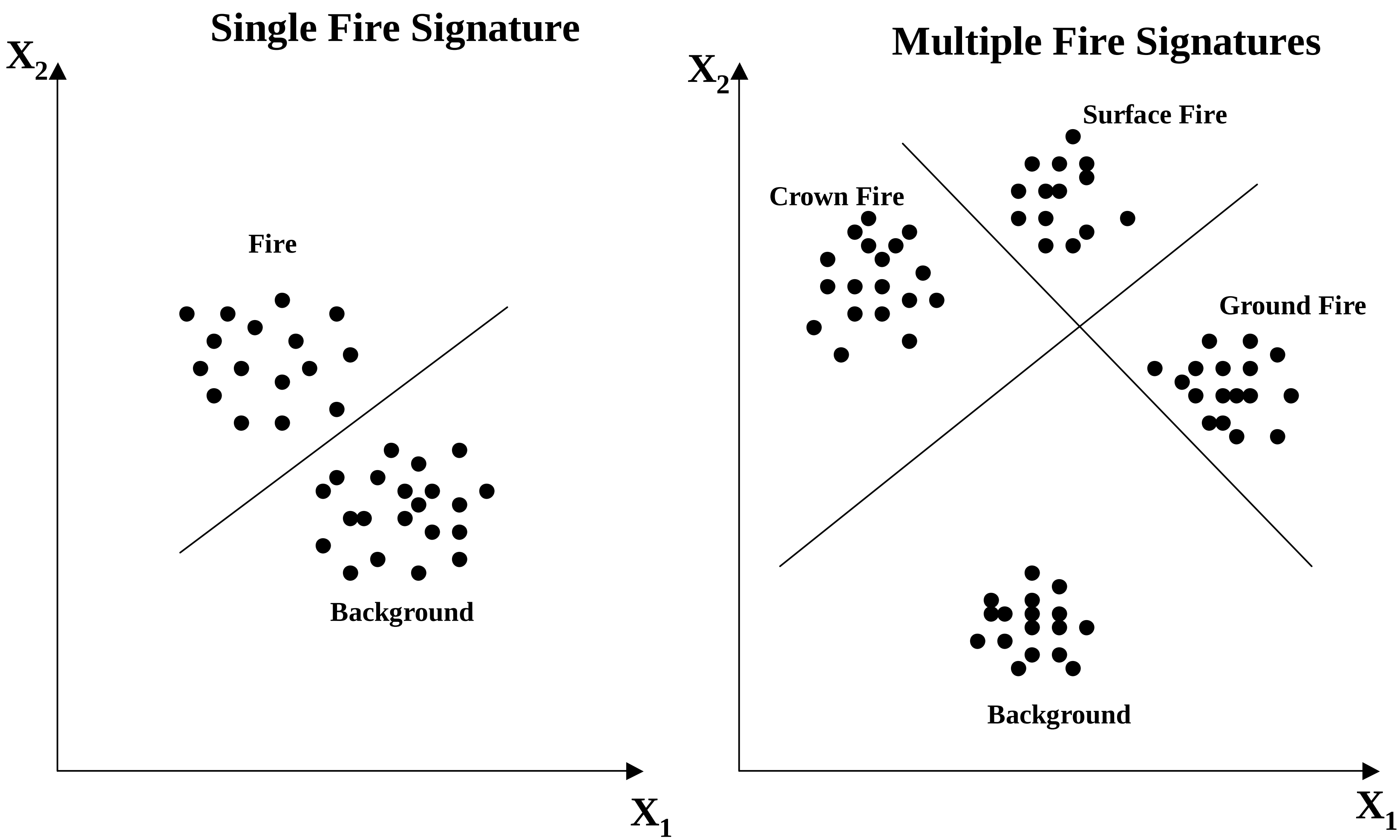


Figure 7 Pixel Time History for a Fire

2003:Day 126, –83.09 Deg W Long, 29.59 Deg N Lat   File: lightcurve_ch2_mycoords_may07.png

Negative finger indicative of strong fire signal

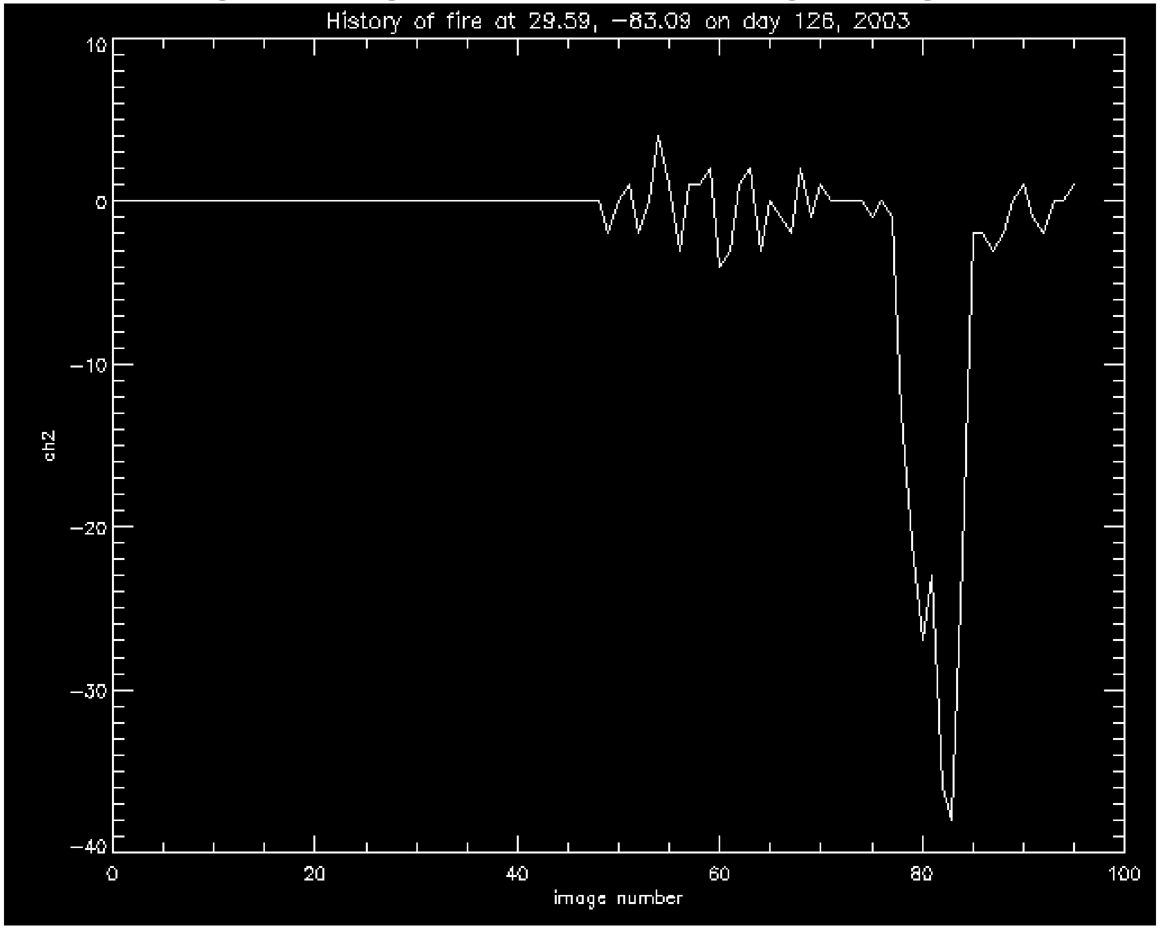


Figure 8 GOES CH2 (3.78 - 4.03 μm) Northern Florida Fire

2003: Day 126 , –82.10 Deg West Longitude, 30.49 Deg North Latitude File: florida_ch2.png

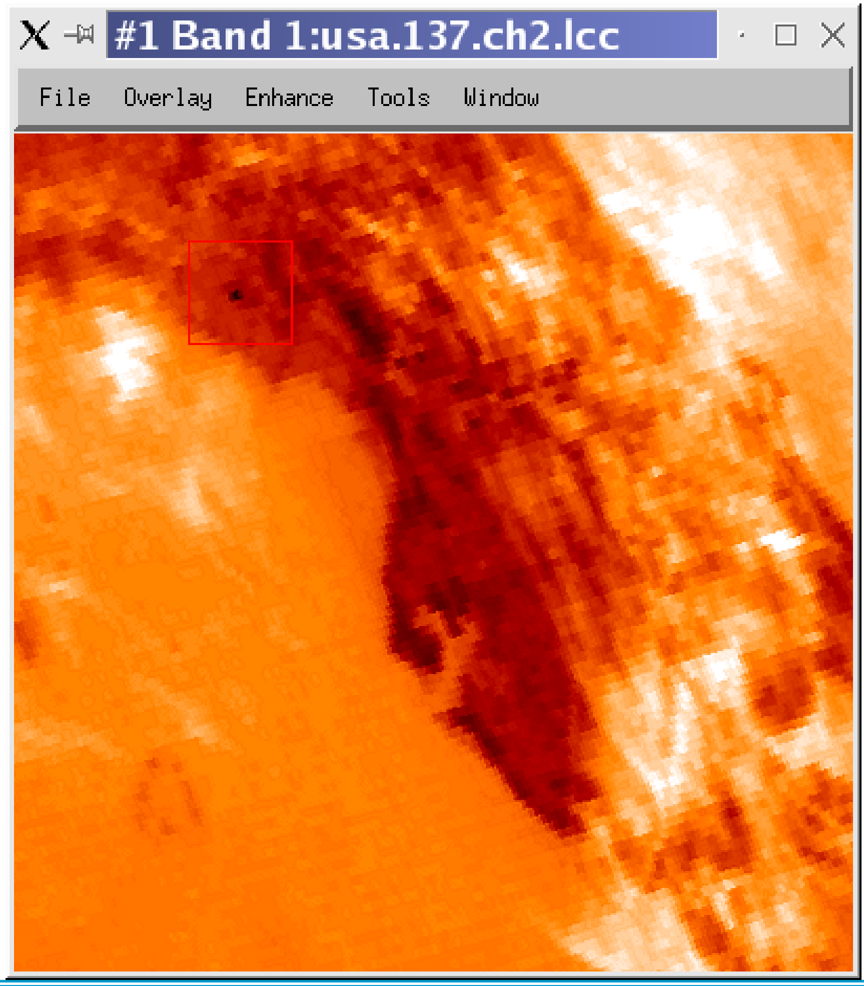
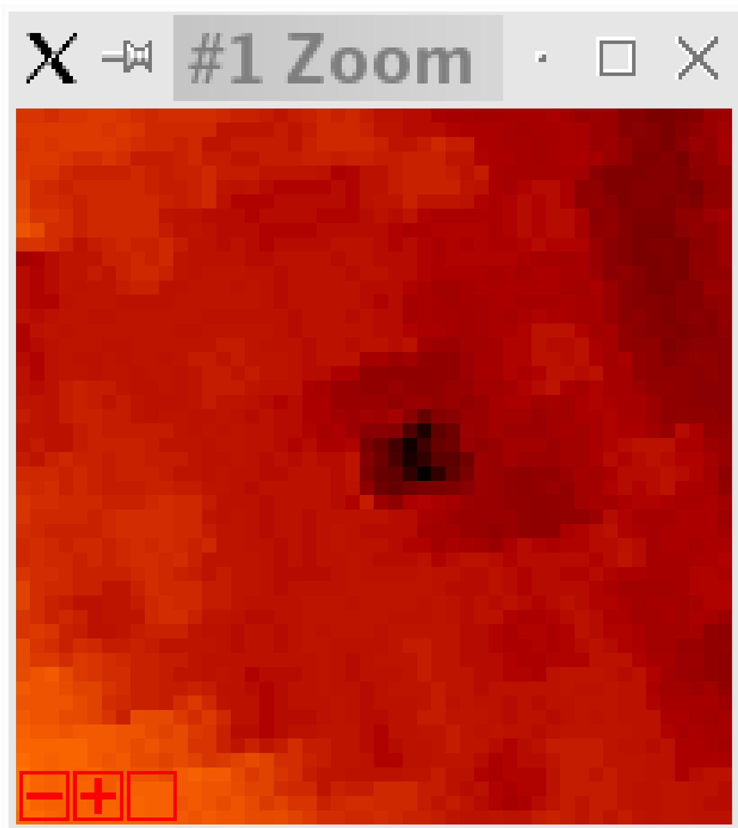


Figure 9 Zoom of GOES CH2 (3.78 - 4.03 µm) Northern Florida Fire

2003:Day 126, –82.10 Deg W Long, 30.49 Deg N Lat

Local minimum in vicinity of core pixel used as fire location.

File: florida_fire_ch2_zoom.png



File: florida_ch2_zoom.png

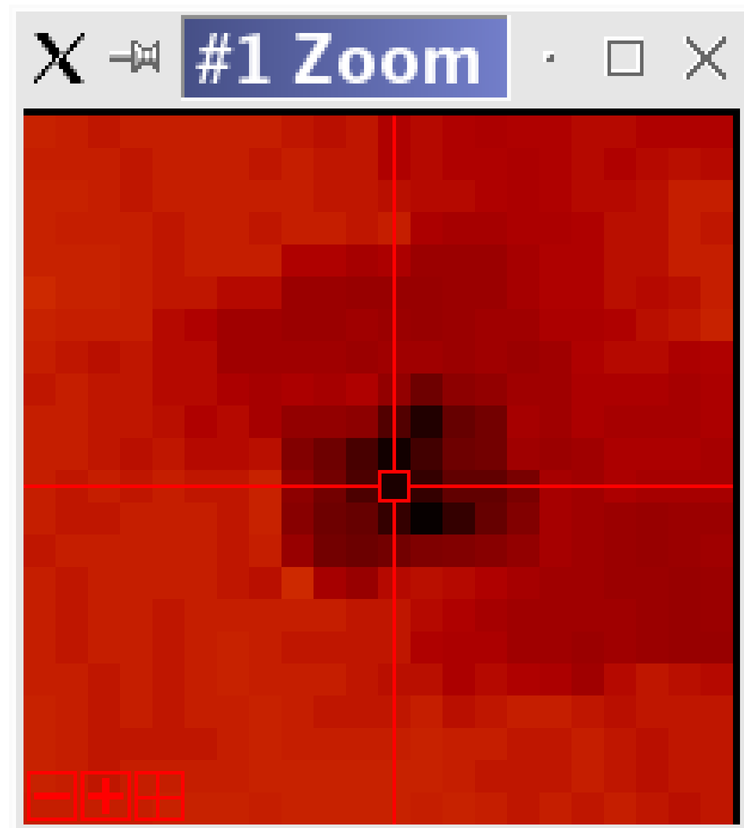
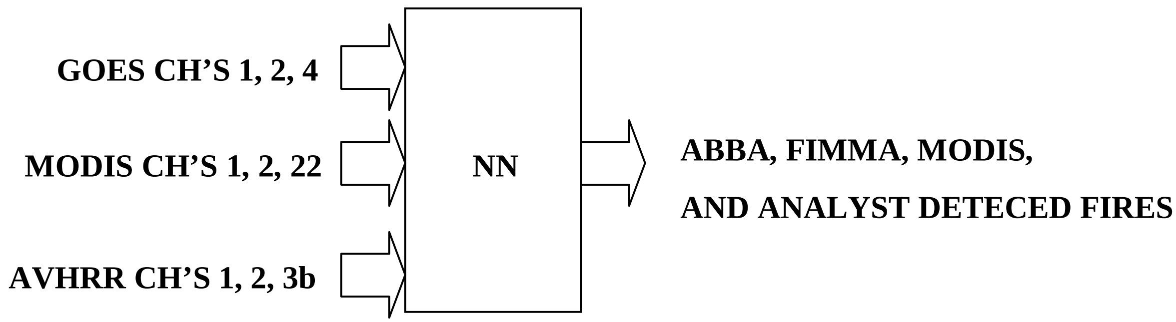


Figure 10 Envisioned Neural Network Configuration



Where

each sensor input is:

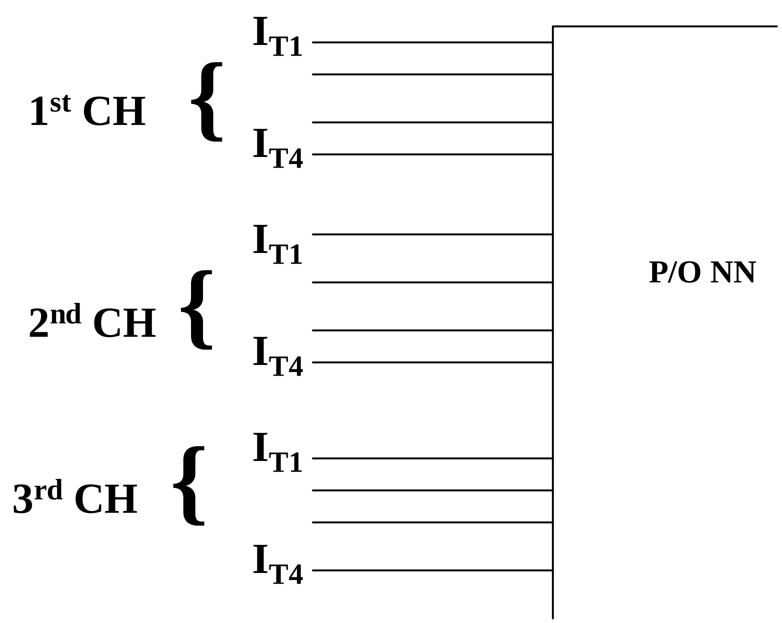
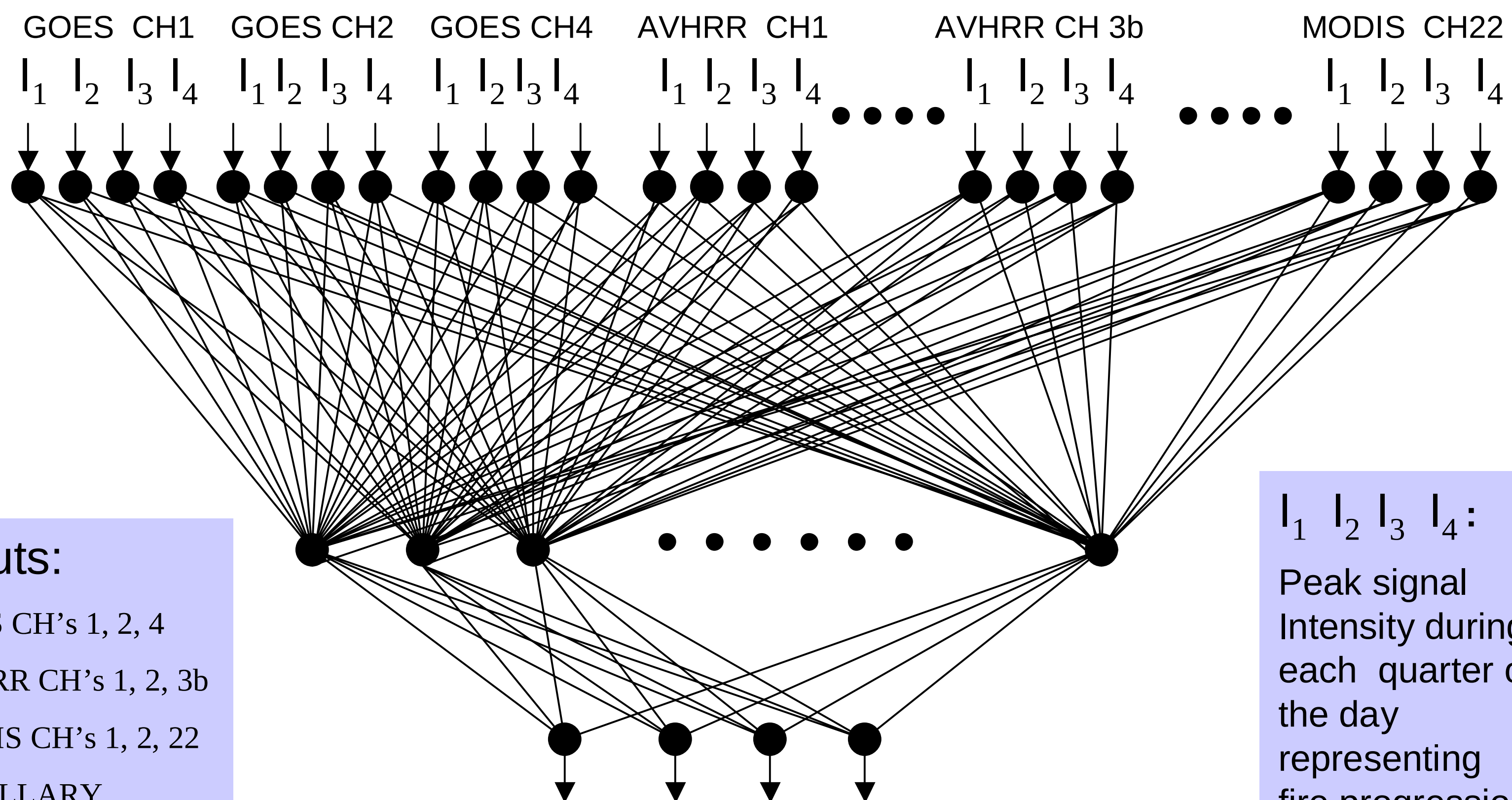


Figure 11 3-Sensor Input Backpropagation Neural Network



‘1’ = FIRE ‘0’ = NONFIRE for

Fimma, Abba, Modis and Analysis Outputs

Inputs:

GOES CH’s 1, 2, 4

AVHRR CH’s 1, 2, 3b

MODIS CH’s 1, 2, 22

ANCILLARY INPUTS (not shown)

(all 8 bit words)

I_1 I_2 I_3 I_4:

Peak signal Intensity during each quarter of the day representing fire progression throughout the day

Figure 12 Scatter Plot of Background-Subtracted GOES CH 1/CH 2

Fire (lower) and non-fire (upper) separation of clusters

2003: June 2 Northern Florida File: scatter_fires12.png

(GOES CH1, CH2, CH4 are input to neural network)

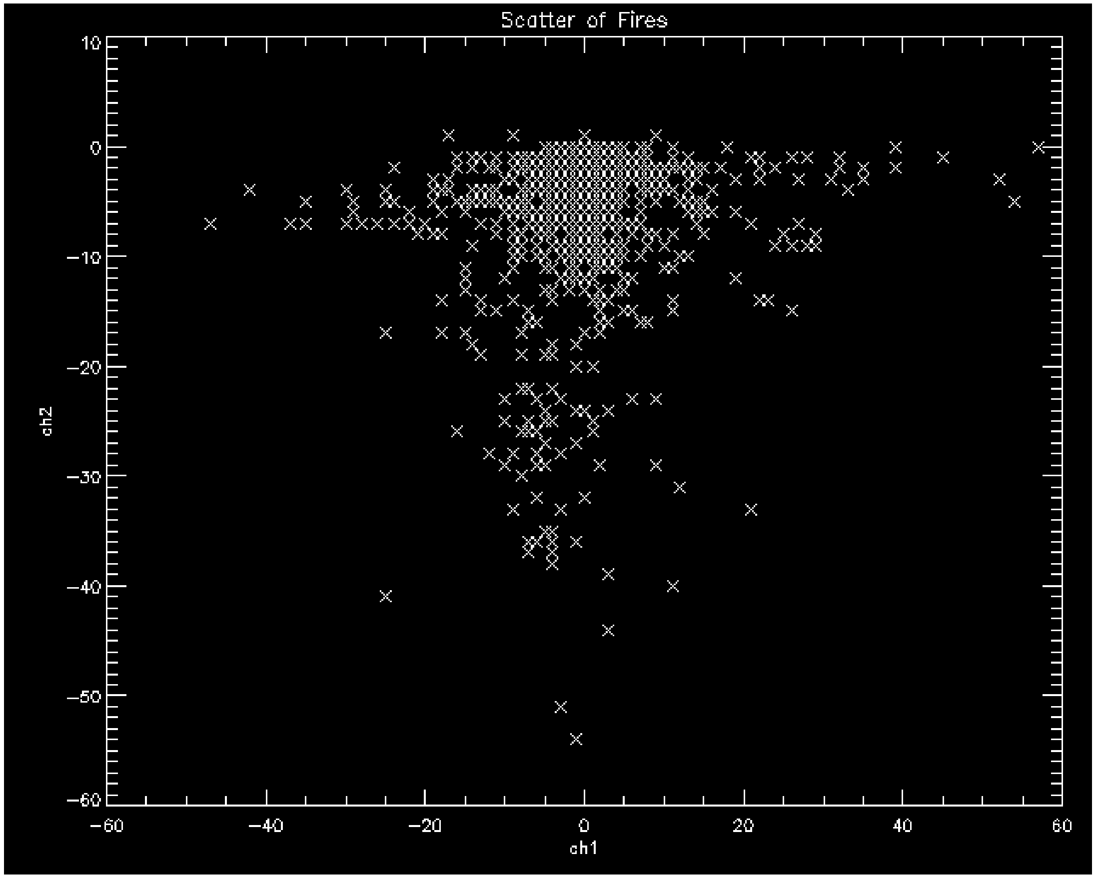
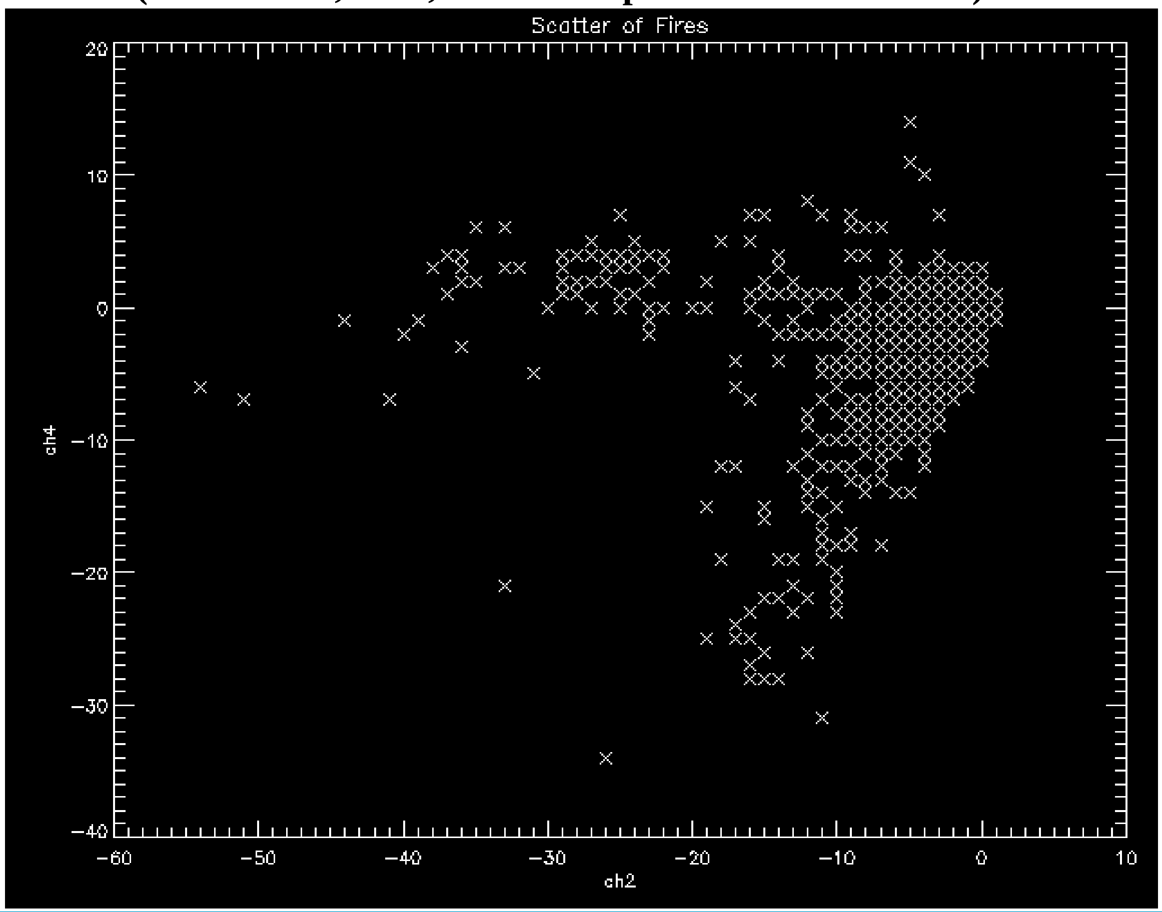


Figure 13 Scatter Plot of Background –Subtracted GOES CH 2/CH 4

Fire (left) and non-fire (right) separation of clusters

2003: June 2 Northern Florida File:scatter_fires22.png

(GOES CH1, CH2, CH4 are input to neural network)



TASK SUMMARY

Neural network software is to be integrated with NOAA NESDIS's Hazard Mapping System (HMS) as an aid in automating the fire detection system and improving consistency. Initial scatter plots (Figures 12, 13) suggest fire is separable from the background with a minimum of 3 spectral channels. A neural network will be trained to recognize fires from 3 spectral channels of GOES, MODIS and AVHRR imagery, mimicking not only the FIMMA (AVHRR), WF-ABBA (GOES) and MODIS automated algorithms but the subjective decision making by NOAA Fire Analysts' as well.

Data reduction has proven to be the most difficult aspect of the task because NOAA's fire product does not permit precise correlation between identified fires and particular sensor images in which they appear. Additionally, HMS fire geographic locations are offset by spacecraft navigational and systemic software errors.

An envisioned neural network architecture is depicted in Figures 10 and 11. Input vectors attempt to characterize fire progression throughout the day by providing a time series input to the network. Early attempts at obtaining neural network convergence during training with these time series vectors have not proven as successful however as vectors which indicate the instantaneous presence or absence of fires. Continuing research requires refining the neural network training process with regard to types of input vectors. Further work is also aimed at determination of the extent of class separation between different categories of fires typical of various land cover types (Figure 6) which will also affect training approaches.